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Frequency Recognition Methods for Dual-frequency SSVEP based Brain-computer Interface

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Abstract— **Dual-frequency steady-state visual evoked potential (SSVEP) was suggested to generate more stimuli using a few flickering frequencies for brain-computer interface. Dual-frequency SSVEP peaks at more than two frequencies—both main and harmonic frequencies. However multi-frequency recognition strategy has not been investigated for dual-frequency SSVEP. In this paper, three modified power spectral density analysis (PSDA) methods and two modified canonical correlation analysis (CCA) methods were tested for dual-frequency SSVEP classification. Three methods among the five methods used conventional features or classification techniques, and the other two methods used modified features for harmonic frequencies. As a result, CCA with novel features showed the best BCI performance. Also the use of harmonic frequencies improved BCI performance of dual-frequency SSVEP.**

I. INTRODUCTION

Electroencephalography (EEG) based brain-computer interface (BCI) allows user to non-invasively interact with the environment without limb movement [1], employing various brain signals such as steady-state visual evoked potential (SSVEP) [2], P300 [3], sensorimotor rhythm (SMR) [4], or auditory responses [5]. Among them, SSVEP-based BCIs has been widely investigated because of its low requirement of training and high BCI performances [2].

SSVEP is periodic evoked potential elicited by a visual stimulus flickering at a constant frequency, showing spectral characteristic that peaks occur at multiple harmonic frequencies such as main, second, or sub harmonic frequency [6]. SSVEP-based BCIs classify SSVEP segments by exploiting the spectral characteristic. The most used frequency recognition methods for SSVEP are power spectral density analysis (PSDA) and canonical correlation analysis (CCA).

PSDA usually uses spectral power or signal-to-noise ratio (SNR) of SSVEP at specific frequency. SSVEP classification is accomplished by choosing the largest value among those of targets [7] or just using linear discriminant analysis (LDA) [8]. Whereas, CCA seeks linear transformation such that correlation between two random variables is maximize. CCA classifies SSVEPs in reference to the correlation coefficient. Because multidimensional sets can be used as the variables, multichannel EEG data can be simply analyzed using CCA [9]. G. Bin et al. compared CCA and PSDA for online multi-channel SSVEP-based BCI, CCA was superior to PSDA [9].

SSVEP peaks appear at stimulus frequency and its harmonics, the number of flickering frequencies should be the same with the number of targets for SSVEP-based BCIs. However, the number of flickering frequencies can be limited in certain conditions (e.g., using a monitor as visual stimuli). K. –K. Shyu et al. recently suggested dual-frequency SSVEP for generating more stimuli with a few flickering frequencies [10]. Through combination of the frequencies, ${}_{N}C_2 + N$ stimuli can be generated using only N flickering frequencies. Contrary to conventional single-frequency SSVEP, dual-frequency SSVEP has peaks at non-integer harmonic frequencies as well as main frequencies. In [10], in response to a dual-frequency stimulus flickering at different frequencies (f_1 and f_2), spectral peaks occurred at the symmetric harmonic frequencies: $2f_1-f_2$ and $2f_2-f_1$. In [11], flickering frequencies for dual-frequency stimulus were in low-frequency band less than 5Hz, and SSVEP peak appeared at the sum of the frequencies. In our previous study, one more harmonic frequency was found at $|f_1-f_2|$.

Even though some research groups reported characteristics of dual-frequency SSVEP, BCI system using the brain response has scarcely been implemented. And to our knowledge, classification strategy for dual-frequency SSVEP has not been investigated using both main and harmonic frequencies. Conventional frequency recognition methods are optimized for single-frequency SSVEP, so modification or a new method is required for dual-frequency SSVEP. The new strategy can exploit the harmonic frequencies as well as main frequencies.

In this paper, modified PSDA and CCA were tested for dual-frequency SSVEP classification. Three methods used conventional features (SNR or correlation) or classification methods (ranking or LDA). The other two methods used modified features contributed by both main and harmonic frequencies, taking advantage of harmonic frequencies.

II. METHODS

A. *Dual-frequency stimulus*

A dual-frequency stimulus was generated as two sine waves at different frequencies (f_1 and f_2). Two LED arrays flickered as the different sine waves respectively, composing a visual stimulus. Diffusion film was attached above the arrays so that subjects could attend the stimulus without focusing on only one side. The flickering frequencies were non-harmonic and in medium frequency range: 19Hz, 23Hz, 27Hz, and 31Hz. Four pairs of them were used as

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dual-frequency stimuli: (19Hz, 27Hz), (19Hz, 31Hz), (23Hz, 27Hz), and (23Hz, 31Hz).

B. Experimental Settings

Total of three subjects (two males and one female) participated in the experiment with informed consent. They had corrected-to-normal vision and no experience or family history of epileptic seizure.

At t=0s, subjects were requested to gaze at the cross in the center of a 26inch monitor (T260HD, Samsung, Korea). When a target was presented at t=3s, subjects had to attend to the relevant LED array for six seconds among the four arrays around the monitor. During attending to the target, eye or jaw movement was not allowed to avoid noise. After a beep at t=9s, subjects could freely move their eye or jaw. Every target was randomly attended for ten times equally. From total of 6s-length EEG analysis, first 0.5s data was rejected to exclude noise generated from eye or neck movement to locate the target.

Two-channel EEG signal was achieved using g.USBamp (g.tec, Austria) at O1 and O2 well known for engaging in SSVEP generation [12]. The reference and ground electrodes were positioned at A1 and Fpz, respectively. The sampling rate was 512Hz, and the high-pass filter at 2Hz and notch filter at 60Hz were applied on the amplifier.

C. Spectral analysis of dual-frequency SSVEP

Spectrum of each target was estimated according to the subjects using g.BSanalyze (g.tec, Austria) to identify harmonic frequencies of dual-frequency SSVEP. The 'spectrum' function first detrended and windowed 5s-length EEG signal, and estimated the square of the value of Fast Fourier Transform (FFT). The power spectral density (PSD) of each target was used to estimate signal-to-noise ratio (SNR) of SSVEP [12]. The SNR was the ratio of PSD at each frequency to the mean PSD of adjacent eight frequencies. Frequency with SNR larger than 3 was identified as peak frequency. Then peak frequencies of each target were compared to find harmonic components of dual-frequency SSVEP. The frequency components commonly found for multiple targets were defined as harmonic components of dual-frequency SSVEP. And every combination of the harmonic frequencies was employed as a feature for multiple frequency recognition. To consider the effect of the main frequencies, the combination always contained the two main frequencies.

D. Power spectral density analysis

Three different frequency recognition methods were devised for PSDA: (1) SNR-ranking, (2) SNR-sum, and (3) SNR+LDA. The SNRs were estimated from an EEG segment of each trial, the length of which was varied from 1s to 5s. The segments were extracted using rectangular window starting at every second of each trial. For example, 1s-segment was extracted from each trial starting at 3.5s, 4.5s, 5.5s, 6.5s, and 7.5s.

The first method was to pick two frequencies out among the four main frequencies (19Hz, 23Hz, 27Hz, and 31Hz) according to SNRs. Four stimulus frequencies were arranged in descending order of SNR. Because every target was composed of combination of two frequencies, first two frequencies in the rank were further compared with the four stimulus frequency pairs. If the two frequencies were 19Hz and 27Hz, the EEG segment was classified as class 1; 19Hz and 31Hz as class 2; 23Hz and 27Hz as class 3; 23Hz and 31Hz as class 4. If the frequencies with the first two largest SNRs did not correspond to any of the stimulus frequency pairs, the class was 0.

The second method was to consider sum of SNRs at the two main frequencies and the harmonic frequencies. The SNR values were summed at the main frequencies ($SNR_{i,f1}$, $SNR_{i,f2}$) and the combination of the harmonic frequencies ($SNR_{i,f\mathrm{harm}}$) according to the class as

$$\mathrm{SNR}_i = \mathrm{SNR}_{i,f1} + \mathrm{SNR}_{i,f2} + \mathrm{SNR}_{i,f\mathrm{harm}}, \qquad i=1,2,3,4$$

where i is the class. Then the class with the largest SNR sum was decided as the target the subject attended. BCI performances (accuracy) were compared according to the 2^N combinations of the N harmonic frequencies. And the best BCI performance among them was compared with that of only the main frequencies.

The last modified PSDA was to apply LDA to features which were SNR values at the main frequencies and the combination of the harmonic frequencies. LDA estimates hyperplanes to separate the data of multiple classes. This technique has a low computational requirement, suitable for the online BCI system [13]. In this study, features for LDA were SNRs of the combination of the harmonic frequencies. Ten-fold cross validation was used, so every EEG segment was randomly divided into ten equal-sized groups. Nine folds trained the classifier and the other fold validated it. This step was repeated until every fold was used as the validation set. BCI performance was estimated as the average accuracy of ten validation sets. For the second and third modified PSDA methods, accuracy of main frequencies was compared with that of the best combination of harmonic frequencies.

E. Canonical correlation analysis

For frequency recognition of SSVEPs, the two variables (X and Y) are usually an EEG segment and a reference signal—*sine* and *cosine* of specific frequency. In this study, an EEG segment was extracted from every trial as mentioned in PSDA.

Two modified CCA were compared for frequency recognition: (1) correlation ranking with a conventional reference signal, (2) CCA with a novel reference signal. First method used a conventional reference signal for CCA. Because it is consisted of *sine* and *cosine* at a specific frequency, simultaneous multi-frequency recognition is not possible. Therefore the reference signal was consisted of *sine* and *cosine* at each stimulus frequency and its second harmonic for the correlation ranking method. We arranged the four stimulus frequencies in order of correlation coefficient between a corresponding reference signal and an EEG segment. For first PSDA method, first two stimulus frequencies with large correlations were compared with four stimulus frequency pairs. For example, if reference signals at 23Hz and 27Hz showed larger correlations with a segment than those at 19Hz and 31Hz, the segment was classified as class 3. If a pair of the two frequencies was not included in the four stimulus frequency pairs, the segment was classified as class 0 and considered as a wrong classification.

Second modified CCA was to use a novel reference signal to simultaneously recognize harmonic components of dual-frequency SSVEP. Compared with conventional way, a novel reference signal was consisted of *sine* and *cosine* at multiple frequencies—two main frequencies, harmonic frequencies, and their second harmonics:

$$Y_{dual} = \begin{pmatrix} \sin(2\pi f_1 t) \\ \cos(2\pi f_1 t) \\ \sin(4\pi f_1 t) \\ \cos(4\pi f_1 t) \\ \vdots \\ \sin(2\pi f_{harm} t) \\ \cos(2\pi f_{harm} t) \\ \sin(4\pi f_{harm} t) \\ \cos(4\pi f_{harm} t) \end{pmatrix}.$$

Four reference signals were generated according to the class, and four correlations in accordance with the reference signals were estimated with an EEG segment. The class with the largest correlation was finally chosen, which was the same with conventional CCA in a manner of classification method. The best performance of the frequency combination was compared with the performance of main frequencies.

F. *Statistical analysis*

Classification accuracy was estimated in terms of features (SNR and canonical correlation), classification methods (ranking, sum, and LDA for PSDA; ranking and using the proposed reference signal for CCA), frequency combinations (main frequencies and harmonic frequencies), and window lengths (1s to 5s). The feature category was to know which feature was better for frequency recognition of dual-frequency SSVEP regardless of classification method. The frequency combination category was divided into using only main frequencies and using both main and harmonic frequencies, verifying advantage of use of harmonic frequencies. The performances were statistically compared using repeated-measures analysis of variance (ANOVA) with 5% significance level.

III. RESULTS

A. *Harmonic frequency*

Peak frequency components were different for targets and subjects. For example, spectrum of target 1 of subject 1 peaked at 19Hz (f_1), 27Hz (f_2), 35Hz ($2f_2 - f_1$), 38Hz ($2f_1$), and 46Hz ($f_1 + f_2$). But spectrum of target 2 of subject 1 peaked at 19Hz (f_1), 31Hz (f_2), 12Hz ($f_2 - f_1$), 57Hz ($3f_1$), and 62Hz ($2f_2$). And spectrum of target 2 of subject 3 peaked at 19Hz (f_1), 23Hz, and 46Hz. Peak frequency components commonly found and related to the main frequencies were defined as harmonic components of dual-frequency SSVEP. The peaks appeared at 23Hz and 46Hz in the spectrum of target 2 of subject 3 were not related to the main frequencies (19Hz and 31Hz), thus they were not considered as harmonic components. Finally four harmonic frequencies were identified as $2f_1 - f_2$, $2f_2 - f_1$, $f_1 + f_2$, and $|f_1 - f_2|$. And sixteen combinations of the four harmonic components were employed for PSDA-sum, PSDA+LDA, and CCA with the novel reference signal.

TABLE I. AVERAGE ACCURACIES IN TERMS OF FEATURES, CLASSIFICATION METHODS, FREQUENCY COMBINATIONS, AND WINDOW LENGTHS

Category	**Subcategory**	**Average accuracy (%)**
Feature	SNR (PSDA)	57.7 ± 13.4
	canonical correlation (CCA)	69.4 ± 16.8
Classification method	PSDA – ranking	31.5 ± 17.6
	PSDA – sum	62.5 ± 13.0
	PSDA + LDA	66.1 ± 11.9
	CCA – ranking	60.0 ± 18.5
	CCA with the novel reference signal	74.1 ± 14.0
Frequency combination	Main frequencies	63.3 ± 13.4
	Harmonic frequencies	71.9 ± 12.8
Window length	1s	43.7 ± 12.5
	2s	58.3 ± 15.4
	3s	63.9 ± 17.5
	4s	70.6 ± 17.1
	5s	74.1 ± 16.4

B. *BCI performance*

Table 1 shows average BCI performance according to four categories and their subcategories. Each value was estimated regardless of the other categories, so the standard deviation was larger than 10. The accuracy difference between features was significant over window lengths ($F(4, 19) = 4.835$, $p < 0.01$); canonical correlation outperformed to SNR by 11.6 ± 3.4 %. The accuracies were also significantly different according to classification methods over window lengths ($F(12, 34.686) = 3.182$, $p < 0.01$). From Tukey's HSD test, PSDA-ranking method was demonstrated as the worst ($p < 0.01$ between PSDA-ranking and CCA-ranking, and $p < 0.001$ between PSDA-ranking and the others). Correct classification rate was higher when using both main and harmonic frequencies than using only main frequencies by 8.6 ± 3.6 % ($p < 0.075$). Lastly, accuracy was significantly different according to window length ($F(4, 19) = 82.870$, $p < 0.001$); as window length increased from 1s to 5s, accuracy got increased by 30.4%.

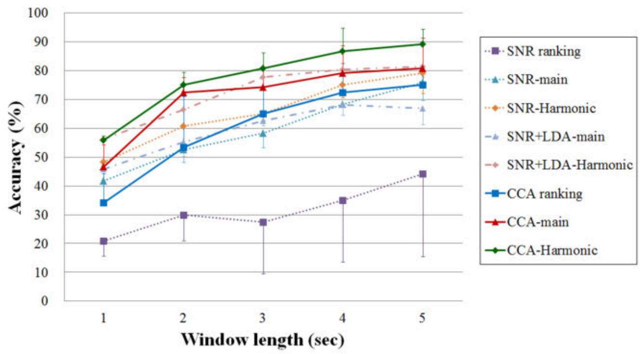

Fig. 1. BCI performance according to classification methods and window lengths

No interaction was found between classification method, frequency combination, and window length ($F(8, 26) = 0.462$, $p > 0.87$). Thus advantage of harmonic frequencies could be confirmed for every classification method and every window length. In Fig. 1, PSDA using harmonic frequencies always outperformed PSDA using only fundamental frequencies; CCA showed the same result. Also an increasing trend of accuracy according to window length was shown for every classification method and every frequency combination (Fig. 1).

IV. Discussion and Conclusion

Five different classification methods were compared for multi-frequency recognition of dual-frequency SSVEP: PSDA-ranking, PSDA-sum, PSDA+LDA, CCA-ranking, and CCA with the novel reference signal. These methods were modifications of conventional PSDA or CCA for multiple frequency recognition. PSDA-ranking, PSDA+LDA, and CCA-ranking accept conventional feature extraction approach of PSDA and CCA, slightly different in classification step. Among the five methods, the modified CCA method was superior to the others. Accuracies were much above the chance level (25%), but that of CCA with the novel reference signal was higher than the others ($p < 0.001$ for PSDA-ranking; $p < 0.13$ for PSDA-sum and CCA-ranking; $p < 0.42$ for PSDA+LDA). These results inferred that CCA with the novel reference—especially using harmonic components— would be better than PSDA for dual-frequency SSVEP as for single-frequency SSVEP [9].

Because conventional PSDA and CCA were used for single frequency recognition, modification was required for multiple frequency recognition. The proposed methods (PSDA-sum and CCA with the novel reference signal) were devised to classify multi-frequency SSVEPs at once. The conventional PSDA or CCA needed at least eight features for four-class classification. Even if all of the features were estimated, pattern classification would be hard because spectral characteristic of dual-frequency SSVEP changes even for the same target. If harmonic components are considered, much more features will be needed. However, no matter how many frequencies were employed, only N features are required to classify N classes for the proposed methods. Also all of the harmonic frequencies contribute to the frequency recognition in the proposed methods, so the method is robust to the change of spectral characteristic (e.g., different peak frequencies for the same target).

The proposed frequency recognition methods were performed for frequency-overlapped multiple targets. But if single-frequency stimuli were added, another strategy would be needed to classify single- and dual-frequency SSVEPs.

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